

Detection and Resolution of Rumours in Social Media: A Survey

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Despite the increasing use of social media platforms for information and news gathering, its unmoderated nature often leads to the emergence and spread of rumours, i.e. pieces of information that are unverified at the time of posting. At the same time, the openness of social media platforms provides opportunities to study how users share and discuss rumours, and to explore how natural language processing and data mining techniques may be used to find ways of determining their veracity. In this survey we introduce and discuss two types of rumours that circulate on social media; long-standing rumours that circulate for long periods of time, and newly-emerging rumours spawned during fast-paced events such as breaking news, where reports are released piecemeal and often with an unverified status in their early stages. We provide an overview of research into social media rumours with the ultimate goal of developing a rumour classification system that consists of four components: rumour detection, rumour tracking, rumour stance classification and rumour veracity classification. We delve into the approaches presented in the scientific literature for the development of each of these four components. We summarise the efforts and achievements so far towards the development of rumour classification systems and conclude with suggestions for avenues for future research in social media mining for detection and resolution of rumours.

1. INTRODUCTION

Social media platforms are increasingly being used as a tool for gathering information about, for example, societal issues [Lazer et al. 2009] and to find out about the latest developments during breaking news stories [Phuvipadawat and Murata 2010]. This is possible because these platforms enable anyone with an Internet-connected device to share in real-time their thoughts and/or to post an update about an unfolding event that they may be witnessing. Hence, social media has become a powerful tool for journalists [Diakopoulos et al. 2012; Tolmie et al. 2017a] but also for ordinary citizens [Hermida 2010]. However, while social media provides access to an unprecedented source of information, the absence of systematic efforts by platforms to moderate posts also leads to the spread of misinformation [Procter et al. 2013b; Webb et al. 2016], which then requires extra effort to establish their provenance and veracity. Updates associated with breaking news stories are often released piecemeal, which gives rise to a significant proportion of those updates being unverified at the time of posting, some of which may later be proven to be false [Silverman 2015a]. In the absence of an authoritative statement corroborating or debunking an ongoing rumour, it is observed that social media users will often share their own thoughts on its veracity via a process of collective, inter-subjective sense-making [Tolmie et al. 2017b] that may lead to the exposure of the truth behind the rumour [Procter et al. 2013a; Li and Sakamoto 2015].

Nevertheless, despite this apparent robustness of social media, its increasing tendency to give rise to rumours motivates the development of systems that, by gathering and analysing the collective judgements of users [Lukasik et al. 2016], are able to reduce the spread of rumours by accelerating the sense-making process [Derczynski and Bontcheva 2014]. A rumour detection system that identifies, in its early stages, postings whose veracity status is unverified, can be effectively used to warn users that the information in them may turn out to be false [Zhao et al. 2015]. Likewise, a rumour classification system that aggregates the evolving, collective judgements posted by users can help track the veracity status of a rumour as it is exposed to this process

of collective sense-making [Metaxas et al. 2015]. In this paper we present an overview of the components needed to develop such a rumour classification system and discuss the success so far of the efforts towards building it.

1.1. Defining and Characterising Rumours

Rumour definition. Recent publications in the research literature have used definitions of rumours that differ from one another. For example, some recent work has mis-defined a rumour as a piece of information that is deemed false (e.g. [Cai et al. 2014; Liang et al. 2015]), while the majority of the literature defines rumours instead as “unverified and instrumentally relevant information statements in circulation” [DiFonzo and Bordia 2007]. In our work, we have adopted as the defining characteristic of rumours that they are unverified at the time of posting, which is consistent with the definition given by major dictionaries, such as the Oxford English Dictionary, which defines a rumour as “a currently circulating story or report of uncertain or doubtful truth”¹ or the Merriam Webster dictionary, which defines it as “a statement or report current without known authority for its truth”². This unverified information may turn out to be true, or partly or entirely false; alternatively, it may also remain unresolved. Hence, throughout this paper we adhere to this prevailing definition of rumour that classifies it as “*a piece of circulating information whose veracity status is yet to be verified at the time of posting*”. A rumour can be understood as a piece of information that has not yet been verified, and hence its truth value remains unresolved while it is circulating.

Rumour types. One may rely on many different factors when classifying rumours by type, including its eventual veracity value (true, false or unresolved) [Zubiaga et al. 2016] or its degree of credibility (e.g. high or low) [Jaeger et al. 1980]. Another attempt at classifying rumours by type is that by [Knapp 1944], who introduced a taxonomy of three types of rumours: (1) ‘pipe-dream’ rumours: i.e. rumours that lead to wishful thinking; (2) ‘bogy’ rumours: i.e. those that increase anxiety or fear; and (3) ‘wedge-driving’ rumours: i.e. those that generate hatred. When it comes to the development of a rumour classification system, the factor that largely determines approaches to be utilised is their temporal characteristics:

- (1) *New rumours that emerge during breaking news.* Rumours that emerge in the context of breaking news are generally rumours that have not been observed before. Therefore, rumours need to be automatically detected and a rumour classification system needs to be able to deal with new, unseen rumours, considering that the training data available to the system may differ from what will later be observed by the system. An example of a rumour that emerges during breaking news is when the identity of a suspected terrorist is reported. A rumour classification system may have observed other similar cases of suspected terrorists, but the case and the names involved will most likely differ. Therefore, the design of a rumour classifier in these cases will need to consider the emergence of new cases, with the new vocabulary that they will likely bring.
- (2) *Long-standing rumours that are discussed for long periods of time.* Some rumours may circulate for long periods of time without their veracity being established with certainty. These rumours provoke significant, ongoing interest, despite (or perhaps because of) the difficulty in establishing the actual truth. This is, for example, the case of the rumour stating that *Barack Obama is muslim*. While this statement is unsubstantiated, it appears that there is no evidence that helps debunk it to the

¹<https://en.oxforddictionaries.com/definition/rumour>

²<http://www.merriam-webster.com/dictionary/rumor>

satisfaction of everyone.³ For rumours like these, a rumour classification system may not need to detect the rumour, as it might be known a priori. Moreover, the system can make use of historical discussions about the rumour to classify ongoing discussions, where the vocabulary is much less likely to differ and therefore the classifier built on old data can still be used for new data.

Throughout the paper we refer to these two types of rumours, describing how different approaches can deal with each of them.

1.2. Studying Rumours: From Early Studies to Social Media

A brief history. Rumours and related phenomena have been studied from many different perspectives [Donovan 2007], ranging from psychological studies [Rosnow and Foster 2005] to computational analyses [Qazvinian et al. 2011]. Traditionally, it has been very difficult to study people’s reactions to rumours, given that this would involve real-time collection of reaction as rumours unfold, assuming that participants had already been recruited. To overcome this obstacle, Allport undertook early investigations [Allport and Postman 1946; 1947] in the context of wartime rumours. He posited the importance of studying rumours, emphasising that “newsworthy events are likely to breed rumors” and that “the amount of rumor in circulation will vary with the importance of the subject to the individuals involved times the ambiguity of the evidence pertaining to the topic at issue”. This led him to set forth a motivational question which is yet to be answered: “Can rumors be scientifically understood and controlled?” [Allport and Postman 1946]. His 1947 experiment [Allport and Postman 1947] reveals an interesting fact about rumour circulation and belief. He looked at how US President Franklin D. Roosevelt allayed rumours about losses sustained by the US Navy at the Japanese attack on Pearl Harbor in 1941. The study showed that before the President made his address, 69% of a group of undergraduate students believed that losses were greater than officially stated; but five days later, the President having spoken in the meantime, only 46% of an equivalent group of students believed this statement to be true. This study revealed the importance of an official announcement by a reputable person in shaping society’s perception of the accuracy of a rumour.

Early research focused on different objectives. Some work has looked at the factors that determine the diffusion of a rumour, including, for instance, the influence of the believability of a rumour on its subsequent circulation, where believability refers to the extent to which a rumour is likely to be perceived as truthful. Early research by Prasad [Prasad 1935] and Sinha [Sinha 1952] posited that believability was not a factor affecting rumour mongering in the context of natural disasters. More recently, however, Jaeger et al. [Jaeger et al. 1980] found that rumours were passed on more frequently when the believability level was high. Moreover, Jaeger et al. [Jaeger et al. 1980] and Scanlon [Scanlon 1977] found the importance of a rumour as perceived by recipients to be a factor that determines whether or not it is spread, the least important rumours being spread more.

Rumours on the Internet. The widespread adoption of the Internet gave rise to a new phase in the study of rumour in naturalistic settings [Bordia 1996] and has taken on particular importance with the advent of social media, which not only provides powerful new tools for sharing information but also facilitates data collection from large numbers of participants. For instance, Takayasu et al. [Takayasu et al. 2015] used social media to study the diffusion of a rumour in the context of the 2011 Japan Earthquake, which stated that rain in the aftermath might include harmful chemical

³Arguably, such rumours survive because they are a vehicle for those inclined to believe in conspiracy theories, where by definition, nothing is as it seems.

substances and led to people being warned to carry an umbrella. The authors looked at retweets of early tweets reporting the rumour, as well as later tweets reporting that it was false. While their study showed that the appearance of later correction tweets diminished the diffusion of tweets reporting the false rumour, the analysis was limited to a single rumour and does not provide sufficient insight into understanding the nature of rumours in social media. Their case study, however, does show an example of a rumour with important consequences for society, as citizens were following the latest updates with respect to the earthquake in order to stay safe.

Rumours in social media. Social media as a source for researching rumours has gained ground in recent years, both because it is an interesting source for gathering large datasets associated with rumours and also because it is a type of platform that gives rise to even more rumours from its many participants. Researchers have used social media, among others, to study how users orient to rumours. It has been generally suggested that Twitter does well in debunking inaccurate information thanks to self-correcting properties of crowdsourcing as users share opinions, conjectures, and evidence. For example, Castillo et al. [Castillo et al. 2013] found that the ratio between tweets supporting and debunking false rumours was 1:1 (one supporting tweet per debunking tweet) in the case of a 2010 earthquake in Chile. Procter et al. [Procter et al. 2013b] came to similar conclusions in their analysis of false rumours during the 2011 riots in England, but they noted that any self-correction can be slow to take effect. In contrast, in their study of the 2013 Boston Marathon bombings, Starbird et al. [Starbird et al. 2014] found that Twitter users did not do so well in distinguishing between the truth and hoaxes. Examining three different rumours, they found the equivalent ratio to be 44:1, 18:1 and 5:1 in favour of tweets supporting false rumours. Delving further into temporal aspects of rumour diffusion and support, [Zubiaga et al. 2016] describe the analysis of rumours circulating during nine breaking news events. This study concludes that, while the overall tendency is for users to support unverified rumours in the early stages, there is a shift towards supporting true rumours and debunking false rumours as time goes on. The ability of social media to aggregate the judgements of a large community of users [Li and Sakamoto 2015] thus motivates further study of machine learning approaches to improve rumour classification systems. Despite the challenges that the spread of rumours and misinformation pose for the development of data mining tools, breaking down the development process into smaller components and making use of suitable techniques is showing encouraging progress towards developing effective systems that can assist people in making decisions towards assessing the veracity of information gathered from social media.

1.3. Scope and Organisation

This survey is motivated by the increasing use of social media platforms such as Facebook or Twitter to post and discover information. While we acknowledge their unquestionable usefulness for gathering often exclusive information, their openness, lack of moderation, and the ease with which information can be posted from anywhere and at anytime undoubtedly leads to major problems for information quality assurance. Given the unease that the spread of rumours can produce and the potential for harm, the incentive for the development of data mining tools for dealing with rumours has increased in recent years. This survey aims to delve into these challenges posed by rumours to the development of data mining applications for gathering information from social media, as well as to summarise the efforts so far in this direction.

We continue this survey in Section 2 by examining the opportunities social media brings to numerous domains, while also introducing the new challenge of having to deal with rumours. Moving on to the analysis of rumour classification systems, we first describe different approaches to putting together a dataset of rumours that enables

further experimentation; the generation of datasets is described in Section 3, beginning with ways for accessing social media APIs, to outlining approaches for collecting and annotating data collected from social media. We summarise findings from studies looking at characterisation and understanding of diffusion and dynamics of rumours in social media in Section 4. After that, we describe the components that form a rumour classification system in Section 5. These components are then further described and existing approaches discussed in subsequent sections; rumour detection systems in Section 6, rumour tracking systems in Section 7, rumour stance classification in Section 8 and veracity classification in Section 9. We continue in Section 10 listing and describing existing applications that deal with the classification of rumours and related applications. To conclude, we summarise the achievements to date and outline future research directions in Section 11.

2. SOCIAL MEDIA AS AN INFORMATION SOURCE: CHALLENGES POSED BY RUMOURS

Social media is being increasingly leveraged by both a range of professionals as well as end users as an information source to learn about the latest developments and current affairs [Van Dijck 2013; Fuchs 2013]. The use of social media has been found useful in numerous different domains; we describe some of the most notable uses below:

News gathering. Social media platforms have shown great potential for news diffusion, occasionally even outpacing professional news outlets in breaking news reporting [Kwak et al. 2010]. This enables, among others, access to updates from eyewitnesses and a broad range of users who have access to potentially exclusive information [Diakopoulos et al. 2012; Starbird et al. 2012]. Aiming to exploit this feature of social media platforms, researchers have looked into the development of tools for news gathering [Zubiaga et al. 2013; Diakopoulos et al. 2012; Marcus et al. 2011], analysed the use of user-generated content (UGC) for news reporting [Hermida and Thurman 2008; Tolmie et al. 2017a], and explored the potential of social media to give rise to collaborative and citizen journalism, including collaborative verification of reports posted in social media [Hermida 2012; Spangenberg and Heise 2014].

Emergencies and crises. The use of social media during emergencies and crises has also increased substantially in recent years [Imran et al. 2015; Castillo 2016; Procter et al. 2013a], with applications such as getting reports from eyewitnesses or finding help-seekers. Social media has been found useful for information gathering and coordination in different situations, including emergencies [Yates and Paquette 2011; Yin et al. 2012; Procter et al. 2013a], protests [Trottier and Fuchs 2014; Agarwal et al. 2014] and natural hazards [Vieweg et al. 2010; Middleton et al. 2014].

Public opinion. Social media is also being used by researchers to collect perceptions of users on a range of social issues, which can then be aggregated to measure public opinion [Murphy et al. 2014]. Researchers attempt to clean social media data [Gao et al. 2014] and try to get rid of population biases [Olteanu et al. 2016] to understand how social media shapes society’s perceptions on issues, products, people, etc. [Goodman et al. 2011]. Social media have been found useful to measure public opinion during elections [Anstead and O’Loughlin 2015], and the effect of online opinions on the offline world is being analysed, for instance, towards the reputation of organisations [Sung and Lee 2015] or towards different policies [Shi et al. 2014].

Financial/stock markets. Social media has also become an important information source to stay abreast of the latest development in the financial world and in stock markets. For instance, sentiment expressed in tweets has been used to predict stock market reactions [Azar and Lo 2016], to collect opinions that investors post in social media [Chen et al. 2014] or to analyse the effect that social media posts can have on brands and products [Lee et al. 2015].

Despite the increasing potential of social media as an information source, its propensity to the spread of misinformation and unsubstantiated claims has given rise to numerous studies on social media. Studies have looked at credibility perceptions of users [Westerman et al. 2014] and have also assessed the degree to which users rely on social media to gather information such as news [Gottfried and Shearer 2016]. The difficulties arising from the presence of rumours and questionable claims in social media has hence led to the study of techniques to build rumour classification systems and to alleviate the problem by facilitating the gathering of accurate information for users. When it comes to the development of rumour classification systems, there are two main use cases to be considered:

- **Dealing with long-standing rumours.** Where the rumours being tracked are known a priori and social media is being mined as a source for collecting opinions. This use case may be applicable, for instance, when one wants to track public opinion, or when rumours such as potential buyouts are being discussed for long periods in the financial domain.
- **Dealing with emerging rumours.** Where new rumours emerge suddenly while certain events or topics are being tracked. This use case may apply in the case of news gathering and emergencies, where information is released piecemeal and needs to be verified, or other suddenly emerging rumours, such as those anticipating political decisions that are expected to have an impact on stock markets.

3. DATA COLLECTION AND ANNOTATION

This section describes different strategies used to collect social media data that enables researching rumours, as well as approaches for collecting annotations for the data.

3.1. Access to Social Media APIs

The best way to access, collect and store data from social media platforms is generally through Application Programming Interfaces (APIs) [Lomborg and Bechmann 2014]. APIs are easy-to-use interfaces that are usually accompanied by documentation that describes how to request the data that one is interested in. They are designed to be accessed by other applications as opposed to web interfaces which are designed for people; APIs provide a set of well-defined methods that an application can invoke to request data. For instance, in a social media platform, one may want to retrieve all data posted by a specific user or all the posts containing a certain keyword.

Before using an API, a crucial first step is to read its documentation and to understand its methods and limitations. Indeed, every social media platform has its own limitations and this is key when one wants to develop a rumour classification system that utilises social media data. Three of the key platforms used for the study of rumours are Twitter, Sina Weibo and Facebook; here we briefly discuss the features and limitations of these three platforms:

- **Twitter** provides detailed documentation⁴ of ways to use its API, which gives access to a REST API to harvest data from its database as well as a streaming API to harvest data in real-time. After registering a Twitter application⁵ that will generate a set of keys for accessing the API through OAuth authentication, the developer will then have access to a range of methods ('endpoints') to collect Twitter data. The most generous of these endpoints gives access to a randomly sampled 1% of the whole tweet stream; getting access to a larger percentage usually requires payment of a fee. To make sure that one gathers a comprehensive collection of tweets, it is

⁴<https://dev.twitter.com/docs>

⁵<https://apps.twitter.com/>

advisable to collect tweets in real-time through the streaming API; again, there is a limit of 1% on the number of tweets that can be collected for free from this API. The main advantage of using Twitter's API is that it is the most open and this may partly explain why it is the most widely used for research; the main caveat is that it is mainly designed to collect either real-time or recent data, and so it is more challenging to collect data that is older than the last few weeks.

- **Sina Weibo**, the most popular microblogging platform in China, provides an API⁶ that has many similarities to that of Twitter. However, access to some of its methods is not openly available. For example the search API requires contacting the administrator to get approval first. Moreover, the range of methods provided by Sina Weibo are only accessible through its REST API and it lacks an official streaming API to retrieve real-time data. To retrieve real-time data from Sina Weibo through its streaming API, one needs to make use of third party providers such as Socialgist⁷⁸.
- **Facebook** provides a documented API⁹ with a set of software development kits (SDKs) for multiple programming languages and platforms that make it easy to develop applications with its data. Similar to Twitter API, Facebook also requires registering an application¹⁰ to generate the keys needed to access the API. In contrast to Twitter, most of the content posted by Facebook users is private and therefore there is no access to specific content posted, unless the users are friends with the authenticated account. The workaround to get access to posts on Facebook is usually to collect data from so-called Facebook Pages, which are open pages created by organisations, governments, groups or associations. Unlike with Twitter, one can then get access to historical data from those Facebook Pages, however, one is limited to content that has been posted in those pages.

In recent years Twitter has become the data source *par excellence* for collection and analysis of rumours, thanks to the openness of its API, as well as its prominence as a source of early reports during breaking news. Most of the research surveyed in this study, as well as the applications described in Section 10, make use of Twitter for this reason.

3.2. Rumour Data Collection Strategies

Collection of social media data that is relevant for the development of rumour classifiers is not straightforward a priori and one needs to define a careful data collection strategy to come up with good datasets. For other applications in social media mining it might just suffice to define filters that are already implemented in the APIs of social media platforms, such as: (1) filtering by keyword to collect data related to an event [Driscoll and Walker 2014]; (2) defining a bounding box to collect data posted from pre-defined geographical locations [Frias-Martinez et al. 2012]; or (3) listing a set of users of interest to track their posts [Li and Cardie 2014]. Collection of rumours requires combining one of those implemented approaches with expertise to retrieve data that is applicable to the rumour classification scenario.

We classify the different data collection strategies employed in the literature in two different levels. On the one hand, researchers have used different strategies to collect long-standing rumours or newly emerging rumours and, on the other hand, re-

⁶<http://open.weibo.com/wiki/API%E6%96%87%E6%A1%A3/en>

⁷<http://www.socialgist.com/>

⁸<http://www.socialgist.com/press/socialgist-emerges-as-the-first-official-provider-of-social-data-from-chinese-microblogging-platform-sina-weibo/>

⁹<https://developers.facebook.com/docs/>

¹⁰<https://developers.facebook.com/docs/apps/register>

searchers have relied on different top-down and bottom-up strategies for sampling rumour-related data from their collections.

Collection of long-standing rumours vs collection of emerging rumours. The methodology for collecting rumour data from social media can have remarkable differences depending on whether the aim is to collect long-standing or newly emerging rumours.

- Collection of long-standing rumours is performed for a rumour or rumours that are known in advance. For instance, posts can be collected for the rumour discussing whether *Obama is muslim or not* by using keywords like *Obama* and *muslim* to filter the posts [Qazvinian et al. 2011]. Since such rumours have, by definition, been running for a while, there is no need to have a system that detects those rumours and the list of rumours is manually input. This type of collection is useful when one wants to track opinion shifts over a long period of time and the ease with which one can define keywords to collect posts enables collection of large-scale datasets. One has to be careful when defining the keywords, so that as many relevant posts as possible are collected.
- Collection of emerging rumours tends to be more challenging. Given that data collection is usually done from a stream of posts in real-time, one needs to make sure that tweets associated with a rumour will be collected before it occurs. Since the keywords are not known beforehand, alternative solutions are generally used for performing a broader data collection to then sample the subset of interest. In closed scenarios where one wants to make sure to collect rumours that emerge during an event or news story, one can simply collect as many posts as possible for those events. Once the posts for an event are collected, one can then filter the tweets that are associated with rumours [Procter et al. 2013b; Zubiaga et al. 2015]; this can be done in two different ways by following top-down or bottom-up strategies, as we explain below. Alternatively, one may want to collect emerging rumours in an open scenario that is not restricted to events or news stories, but in a broader context. A solution for this is to use alternative API endpoints to collect posts through a less restrictive stream of data, such as Twitter’s streaming API sampling a random 1% of the whole, or a filter of posts by geolocation, where available, to collect posts coming from a country or region [Han et al. 2014]. A caveat to be taken into account is that, since the data collection has not been specifically set up for a rumour but for a wider collection, the sampled subset associated with rumours may not lead to comprehensive representations of the rumours as keywords different to those initially predefined can be used. The identification of changes in vocabulary during an event for improved data collection is, however, an open research issue [Earle et al. 2012; Wang et al. 2015].

Top-down vs bottom-up data sampling strategies. Where one collects a broad collection, as can be the case when attempting to discover newly emerging rumours, for instance, collecting posts related to an event or by following an unfiltered stream of posts, it is then often necessary to sample the data to extract the posts associated with rumours. This sampling can be performed by using either a top-down or a bottom-up strategy:

- Top-down sampling strategies prevailed in early work on social media rumours, i.e., sampling posts related to rumours identified in advance. This can apply to long-standing rumours, where one can define keywords to sample posts related a rumour known to have been circulating for a long time [Qazvinian et al. 2011], for retrospective sampling of rumours known to have emerged during an event [Procter et al. 2013b], or using rumour repositories like Snopes.com to collect posts associ-

ated with those rumours [Hannak et al. 2014]. The main caveat of this approach is that sampling of data is limited to the rumours listed and other rumours may be missed.

- Bottom-up sampling strategies have emerged more recently in studies that aimed at collecting a wider range of rumours, i.e., sifting through data to identify rumours, rather than rumours that are already known. Instead of listing a set of known rumours and filtering tweets related to those, the bottom-up collection consists in displaying a timeline of tweets so that an annotator can go through those tweets, identifying the ones that are deemed rumourous. This is an approach that was used first by [Zubiaga et al. 2016] and subsequently by [Giasemidis et al. 2016]. The benefit of this approach is that it leads to a wider range of rumours than the top-down strategy, as it is more likely to find new rumours that would not have been found otherwise. The main caveat of this approach is that generally leads to a few tweets associated with each rumour, rather than a comprehensive collection of tweets linked to each rumour as with the top-down strategy.

3.3. Annotation of Rumour Data

The annotation of rumour data can be carried out at different levels, depending on the task and the purpose. Here we present previous efforts on rumour annotation for different purposes. The first step is to identify the rumourous subset within the collected data. This is sometimes straightforward as only rumourous data is collected using top-down sampling strategies, and hence no further annotation is needed to identify what is a rumour and what is not. However, if one wants to use a bottom-up sampling strategy, then manual annotation work is needed to identify what constitutes a rumour and what a non-rumour [Zubiaga et al. 2015]. Manual distinction of what is a rumour may not always be straightforward, as it is largely dependent on the context and on one's judgement as to whether the underlying information was verified or not at the moment of posting. However, well established definitions of rumour exist to help in this regard [DiFonzo and Bordia 2007] and people with a professional interest in veracity, such as journalists, have put together detailed guides to help determine what is a rumour [Silverman 2015a] and when further verification is needed [Silverman 2013]. Annotation work distinguishing rumours and non-rumours is described in [Zubiaga et al. 2016b] as a task to determine when a piece of information has not sufficient evidence to be verified or lacks confirmation from an authoritative source.

Once rumours and non-rumours have been manually classified, further annotation is usually useful to do additional classification and resolution work on the rumours. It is usually the case that no additional annotations are collected for non-rumours, as the rumours are the ones that need to be further dealt with; different annotations that have been done on rumours including the following:

- **Rumour veracity:** Manually determining the veracity of a rumour is a challenging task, usually requiring an annotator with expertise who performs careful analysis of claims and additional evidence, context and reports from authoritative sources before making a decision. This annotation process has been sometimes operationalised by enlisting the help of journalists with expertise in verification [Zubiaga et al. 2016]. In this example, journalists analysed rumourous claims spreading on social media during breaking news to determine, where possible, if a rumour had later been confirmed as true or debunked and proven false; this is, however, not always possible and some rumours were marked as *unverified* as no reliable resolution could be found. While this approach requires expertise that can be hard to resource, others have used online sources to determine the veracity of rumours. For instance, [Hannak et al. 2014] used Snopes.com as a database that provides ground truth an-

notations of veracity for rumours put together by experts. While some online sources like Truth-O-Meter and PolitiFact provide finer-grained labels for veracity, such as *mostly true*, *half true* and *mostly false*, these are usually reduced to three labels [Popat et al. 2016], namely *true*, *false* and optionally *unverified*. While annotation is increasingly being performed through crowdsourcing platforms for many natural language processing and data mining tasks [Doan et al. 2011; Wang et al. 2013], it is not as suitable for more challenging annotation tasks such as rumour veracity. Crowdsourcing annotations for veracity will lead to collection of credibility perceptions rather than ground truth veracity values, given that verification will often require an exhaustive work of checking additional sources for validating the accuracy of information, which may be beyond the expertise of average crowd workers. This is what [Zubiaga and Ji 2014] found in their study, suggesting that verification work performed by crowd workers tends to favour selection of true labels for inaccurate information.

- **Stance towards rumours:** Annotation of stance involves determining how a social media post is oriented towards a target, the target being a rumour in this case. This has been operationalised by [Qazvinian et al. 2011] annotating tweets as *supporting*, *denying* or *querying* a rumour, while later work by [Procter et al. 2013b] suggested the inclusion of an additional label, *commenting* to make it a scheme with four labels.
- **Rumour relevance:** Annotation of relevance involves determining if a social media post is related to a rumour or not. This is performed as binary classification marking a post as relevant or not. [Qazvinian et al. 2011] annotated rumours by relevance, where for instance for a rumour saying that *Obama is muslim*, a post that says *Obama does seem to be muslim* would be marked as relevant, while a post saying that *Obama had a meeting with muslims* would be marked as not relevant.
- **Other factors:** Some work has performed annotation of additional factors that can be of help in the assessment of the veracity of rumours. For example, [Zubiaga et al. 2016] annotated rumourous tweets for certainty (certain, somewhat certain, uncertain) and evidentiality (first-hand experience, inclusion of URL, quotation of person/organisation, link to an image, quotation of unverifiable source, employment of reasoning, no evidence), along with support. [Lendvai et al. 2016a] annotated relations between claims associated with rumours, intended for automated identification of entailment and contradiction between claims. Annotation of credibility perceptions has also been done in previous work, determining how credible claims appear to people [Mitra and Gilbert 2015; Zubiaga and Ji 2014]; this could be useful in the context of rumours to identify those that are likely to be misleading for people, however, it has not yet been applied in the context of rumours.

4. CHARACTERISING RUMOURS: UNDERSTANDING RUMOUR DIFFUSION AND FEATURES

Numerous recent studies have looked at characterising the emergence and spread of rumours in social media. Insights from these studies can in turn be useful to inform the development of rumour classification systems. Some of this research has focused on extensive analyses of a specific rumour, whereas others have looked into larger sets of rumours to perform broader analyses.

Studies of discourse surrounding rumours have been conducted to examine discussions around – and the evolution of – rumours over time. Some studies have looked at defining a scheme to categorise types of reactions expressed towards rumours. [Maddock et al. 2015] looked at the origins and changes of rumours over time, which led to the identification of seven behavioural reactions to rumours: misinformation, speculation, correction, question, hedge, unrelated, or neutral/other. Similarly, [Procter et al. 2013b] suggested that reactions to rumours could be categorised into four types,

namely support, denial, appeal for more information and comment. Others have looked into rumours to understand how people react to them. By looking at rumours spreading in the Chinese microblogging platform Sina Weibo, [Liao and Shi 2013] identified interventions of seven types of users (celebrity, certified, mass media, organisation, website, internet star and ordinary), who contributed in seven different ways (providing information, giving opinions, emotional statements, sense-making statements, interrogatory statements, directive statements and digressive statements). In another study looking at conversations sparked by rumours on Twitter, [Zubiaga et al. 2016] found that the prevalent tendency of social media users is to support and spread rumours, irrespective of their veracity value. This includes users of high reputation, such as news organisations, who tend to favour rumour support in the early stages of rumours, issuing a correction statement later where needed. In an earlier study, [Mendoza et al. 2010] had found strong correlations between rumour support and veracity, showing that a majority of users support true rumours, while a higher number of users denies false rumours. Despite the apparent contradiction between these studies, it is worth noting that [Mendoza et al. 2010] looked at the entire life cycle of a rumour and hence the aggregation leads to good correlations; in contrast, [Zubiaga et al. 2016] focused on the early reactions to rumours, showing that users have problems in determining veracity in the early stages of a rumour. Using rumour data from Reddit, differences across users have also been identified, suggesting three different user groups: those who generally support a false rumour; those who generally refute a false rumour; and those who generally joke about false rumours [Dang et al. 2016a]. It has also been suggested that corrections are usually issued by news organisations and they can be sometimes widely spread [Takayasu et al. 2015; Arif et al. 2016; Andrews et al. 2016], especially if those corrections come from like-minded accounts [Hannak et al. 2014] and occasionally even leading to deletion or unsharing of the original post [Frias-Martinez et al. 2012]. However, corrections do not always have the same effect as the original rumours [Lewandowsky et al. 2012; Shin et al. 2016; Starbird et al. 2014], which reinforces the need to develop rumour classification systems that deal with newly emerging rumours.

Other studies have looked at factors motivating the diffusion of rumours. Rumour diffusion is often dependent on the strength of ties between users, where rumours are more likely to be spread across strong ties in a network [Cheng et al. 2013]. Other studies looking at temporal patterns of rumours have suggested that their popularity tends to fluctuate over time in social media [Kwon et al. 2013; Kwon and Cha 2014; Lukasik et al. 2015b] and other platforms on the Internet [Jo 2002], but with a possibility of being discussed again later in time after rumour popularity fades.

Studies have also looked at the emergence of rumours. By using rumour theoretic approaches to examine factors that lead to expression of interest in tracking a rumour, [Oh et al. 2013] identified the lack of an official source and personal involvement as the most important factors, whereas other factors, such as anxiety, were not as important. The poster's credibility and attractiveness of the rumour are also believed to be factors contributing to the propagation of rumours [Petty and Cacioppo 2012]. [Liu et al. 2014] reinforced these findings suggesting that personal involvement was the most important factor. Analysing specific rumour messages on Twitter, [Chua et al. 2016] identified that tweets from established users with a larger follower network were spread the most.

While many studies have explored the diffusion of rumours, an exhaustive analysis of these studies is not within the scope of this survey, which focuses instead on research concerning development of approaches to detect and resolve rumours. To read more about studies looking at the diffusion of rumours, we recommend the surveys by [Serrano et al. 2015] and [Walia and Bhatia 2016].

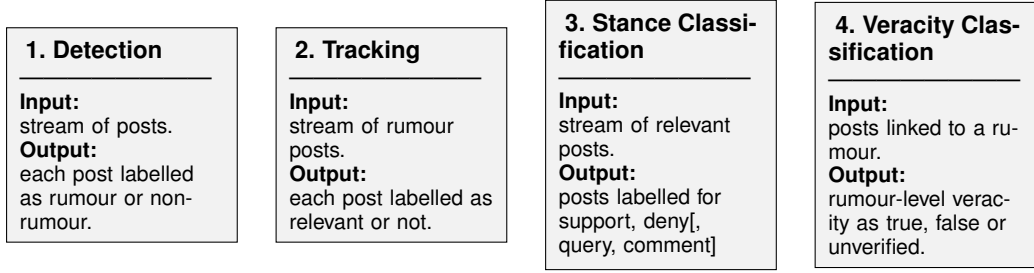


Fig. 1. Architecture of a rumour classification system.

5. RUMOUR CLASSIFICATION: SYSTEM ARCHITECTURE

The architecture of a rumour classification system can have slight variations depending on the specific use case. Here we define a typical architecture for a rumour classification system, which includes all the components needed for a complete system; however, as we point out in the descriptions below, depending on requirements, some of these components can be omitted. A rumour classification system usually begins with identifying that a piece of information is not confirmed (i.e., rumour detection) and ends by determining the estimated veracity value of that piece of information (i.e., veracity classification). The entire process from rumour detection to veracity classification is performed through the following four components (see Figure 1):

- (1) **Rumour detection:** In the first instance, a rumour classification system has to identify whether a piece of information constitutes a rumour. A typical input to a rumour detection component can be a stream of social media posts, whereupon a binary classifier has to determine if each post is deemed a rumour or a non-rumour. The output of this component is the stream of posts, where each post is labelled as rumour or non-rumour. This component is useful for identifying emerging rumours, however, it is not necessary when one needs to deal with rumours that are known a priori.
- (2) **Rumour tracking:** Once a rumour is identified, either because it is known a priori or because it is identified by the rumour detection component, the rumour tracking component collects and filters posts discussing the rumour. Having a rumour as input, which can be a post or a sentence describing it, or a set of keywords, this component monitors social media to find posts discussing the rumour, while eliminating irrelevant posts. The output of this component is a collection of posts discussing the rumour.
- (3) **Stance classification:** While the rumour tracking component retrieves posts related to a rumour, the stance classification component determines how each post is orienting to the rumour's veracity. Having a set of posts associated with the same rumour as input, it outputs a label for each of those posts, where the labels are chosen from a generally predefined set of types of stances. This component can be useful to facilitate the task of the subsequent component dealing with veracity classification. However, it can be omitted where the stance of the public is not considered useful, e.g., cases solely relying on input from experts or validation from authoritative sources.
- (4) **Veracity classification:** The final, veracity classification component attempts to determine the actual truth value of the rumour. It can use as input the set of posts collected in the rumour tracking component, as well as the stance labels produced in the stance classification component. It can optionally try to collect additional data from other sources such as news media, or other websites and databases.

The output of the component can be just the predicted truth value, but it can also include context such as URLs or other data sources that help the end user assess the reliability of the classifier by double checking with relevant sources.

In the following sections, we explore these four components in more detail, the approaches that have been used so far to implement them and the achievements to date.

6. RUMOUR DETECTION

6.1. Definition of the Task and Evaluation

The rumour detection task is that in which a system has to determine, from a set of social media posts, which ones are reporting rumours, and hence are spreading information that is yet to be verified. Note that the fact that a tweet constitutes a rumour does not imply that it will later be deemed true or false, but instead that it is unverified at the time of posting. Formally, the task takes a timeline of social media posts $TL = \{t_1, \dots, t_{|TL|}\}$ as input, and the classifier has to determine whether each of these posts, t_i , is a rumour or a non-rumour by assigning a label from $Y = \{R, NR\}$. Hence, the task is usually formulated as a binary classification problem, whose performance is evaluated by computing the precision, recall and F1 scores for the target category, i.e., rumours.

6.2. Datasets

The only publicly available dataset is the PHEME dataset of rumours and non-rumours¹¹, which includes a collection of 1,972 rumours and 3,830 non-rumours associated with five breaking news stories [Zubiaga et al. 2016b].

6.3. Approaches to Rumour Detection

Despite the increasing interest in analysing rumours in social media and building tools to deal with rumours that had been previously identified [Seo et al. 2012; Takahashi and Igata 2012], there has been very little work in automatic rumour detection. Some of the work in rumour detection [Qazvinian et al. 2011; Hamidian and Diab 2015; 2016] has been limited to finding rumours known a priori. They feed a classifier with a set of predefined rumours (e.g. *Obama is muslim*), which classifies new tweets as being related to one of the known rumours or not (e.g. *I think Obama is not muslim* would be about the rumour, while *Obama was talking to a group of muslims* wouldn't). An approach like this can be useful for long-standing rumours, where one wants to identify relevant tweets to track the rumours that have already been identified; in this survey we refer to this task as *rumour tracking*, as one is aware of the rumours that are being monitored, however, the stream of posts needs to be filtered. Solely relying on a *rumour tracker* would not suffice for fast-paced contexts such as breaking news, where new, unseen rumours emerge and one does not know a priori the specific keywords linked to a rumour, which is yet to be detected. To deal with this, a classifier will need to learn generalisable patterns that will help identify rumours during emerging events.

The first work that tackled the detection of new rumours is that by [Zhao et al. 2015]. Their approach builds on the assumption that rumours will provoke tweets from skeptic users who question or enquire about their veracity; the fact that a piece of information has a number of enquiring tweets associated would then imply that the information is rumourous. The authors created a manually curated list of five regular expressions (e.g., “is (that | this | it) true”) that are used to identify enquiring tweets. These enquiring tweets are then clustered by similarity, each cluster being ultimately

¹¹https://figshare.com/articles/PHEME_dataset_of_rumours_and_non-rumours/4010619

deemed a candidate rumour. It was not viable for them to evaluate by recall, but their best approach achieved 52% and 28% precision for two datasets.

In contrast, [Zubiaga et al. 2016b] suggested an alternative approach that learns context throughout a breaking news story to determine if a tweet constitutes a rumour. They build on the hypothesis that a tweet alone may not suffice to know if its underlying story is a rumour, due to the lack of context. Moreover, they avoid the reliance on enquiring tweets, which they argue that not all rumours may trigger and hence may lead to low recall, as rumours not provoking enquiring tweets would be missed. Their context-learning approach relied on Conditional Random Fields (CRF) as a sequential classifier that learns the reporting dynamics during an event, so that the classifier can determine, for each new tweet, whether it is or not a rumour based on what has been seen so far during the event. Their approach led to improved performance over the baseline classifier by [Zhao et al. 2015], improving also a number of non-sequential classifiers compared as baselines, with a performance of 0.607 in terms of F1 score. The classifier achieved 0.667 in precision and 0.556 in recall, compared to 0.410 and 0.065 respectively for the classifier by [Zhao et al. 2015].

Work by [Tolosi et al. 2016] using feature analysis on rumours across different events found it difficult to distinguish rumours and non-rumours as features change dramatically across events. These findings at the tweet level were then resolved by [Zubiaga et al. 2016b] showing that generalisability can be achieved by leveraging context of the events.

[McCreadie et al. 2015] studied the feasibility of using a crowdsourcing platform to identify rumours and non-rumours in social media, finding that the annotators achieve high inter-annotator agreement. They also categorised rumours into six different types: Unsubstantiated information, disputed information, misinformation/disinformation, reporting, linked dispute and opinionated. However, their work was limited to crowdsourced annotation of rumours and non-rumours and they did not study the development of an automated rumour detection system. The dataset from this research is not publicly available.

Yet other work has been labelled as rumour detection, focusing on determining if information posted in social media was true or false, rather than on early detection of unverified information and hence we discuss this in Section 9 on veracity classification.

7. RUMOUR TRACKING

7.1. Definition of the Task and Evaluation

The rumour tracking component is triggered once a rumour is detected and consists in identifying subsequent posts associated with the rumour being monitored. The input is usually a stream of posts, which can be tailored to the rumour in question after filtering for relevant keywords, or it can be broader by including posts related to a bigger event or even an unrestricted stream of posts. The task is generally framed as a binary classification task that consists in determining whether each of the posts is related to the rumour or not. The output will be a labelled version of the stream of posts, where labels define if each post is *related* or *unrelated*.

Traditional evaluation methods for binary classification are used for this task, namely precision, recall and F1 score, where the positive class is the set of *related* posts.

7.2. Datasets

The most widely used dataset for rumour tracking is that by [Qazvinian et al. 2011], which includes over 10,000 tweets, associated with 5 different rumours, each tweet annotated for relevance towards the rumour as *related* or *unrelated*. *Unrelated* tweets

have similar characteristics to those *related*, such as overlapping keywords, and therefore the classification is more challenging.

While not specifically intended for rumour tracking, the dataset produced by [Zubiaga et al. 2016] provides over 4,500 tweets categorised by rumour. This dataset is different as it does not include tweets with similar characteristics that are actually *unrelated*. Instead, it provides tweets that are associated with different rumours and tweets that have been grouped by rumour.

7.3. Approaches to Rumour Tracking

Research in rumour tracking is scarce in the scientific literature. Despite early work by [Qazvinian et al. 2011] performing automated rumour tracking, few studies have subsequently followed their line of research when it comes to determining the relevance of tweets to rumours. [Qazvinian et al. 2011] use a manually generated Twitter data set containing 10K tweets to guide a supervised machine learning approach. The authors use different features categorised as “content”, “network” and “Twitter specific memes”. The content category contains unigrams, bigrams and their part-of-speech (POS) tags as features. In the network category the authors look at retweets (RT) as a feature. Finally, the Twitter specific memes include content features inferred from hashtags and URLs. A Bayesian classifier is used as the machine learning approach. The best performance was achieved by using content-based features, with a mean average precision of 96.5%.

Later work by [Hamidian and Diab 2015] also focused on a rumour tracker, using the dataset produced by [Qazvinian et al. 2011]. They used an approach called Tweet Latent Vector (TLV), which creates a latent vector representative of a tweet to overcome the limited length and context of a tweet. Their approach relies on the Semantic Textual Similarity (STS) model proposed by [Guo and Diab 2012], which exploits WordNet [Miller 1995], Wiktionary¹² and Brown clusters [Brown et al. 1992] to enhance the shortage of semantic meaning of a tweet. This approach led to a precision score of 97.2%, outperforming the baseline score established earlier by [Qazvinian et al. 2011].

Rumour tracking has not been studied for emerging rumours. The most relevant work to that of tracking newly emerging rumours is that conducted for event detection and tracking in social media [Jaidka et al. 2016]. For instance, [Sayyadi et al. 2009] describe an event detection and tracking approach based on keyword graphs. They build a graph of keywords to detect communities and subsequently newly emerging events. They then use the set of keywords associated with an event to track new incoming tweets. Similar approaches to event tracking have been introduced by others, such as using a bipartite graph for topical word selection [Long et al. 2011], using text classification techniques to determine whether incoming data is related to a previously identified event or to a new one [Reuter and Cimiano 2012], and using similarity metrics [Tzelepis et al. 2016]. However, these approaches have not been directly applied to rumours and hence their applicability needs to be further studied with a suitable rumour dataset.

8. RUMOUR STANCE CLASSIFICATION

8.1. Definition of the Task and Evaluation

The rumour stance classification task consists in determining the type of orientation that each individual post expresses towards the disputed veracity of a rumour. The task is especially interesting in the context of social media, where unverified reports are continually being posted and discussed, both on breaking news stories as

¹²<https://www.wiktionary.org/>

they unfold as well as on long-standing rumours. A rumour stance classifier usually takes a set of rumours $D = \{R_1, \dots, R_n\}$, where each rumour is composed of a collection of posts discussing it. Each rumour has a variably sized set of posts t_i discussing it so that $R_i = \{t_1, \dots, t_{|R_i|}\}$; the task consists in determining the stance of each of the posts t_j pertaining to a rumour R_i . The classification scheme to determine the stance of each post varies across different studies; while early work [Qazvinian et al. 2011] performed 2-way classification of $Y = \{\text{supporting}, \text{denying}\}$, later work performed 3-way classification [Lukasik et al. 2015a] involving $Y = \{\text{supporting}, \text{denying}, \text{querying}\}$ as well as 4-way classification [Zubiaga et al. 2016a] into $Y = \{\text{supporting}, \text{denying}, \text{querying}, \text{commenting}\}$.

The evaluation of the rumour stance classifier is usually based on micro-averaged precision, recall and F1 scores, as well as accuracy scores. However, as research has progressed into a 4-way classification, which generally shows a skewed distribution of labels, evaluation is now also focusing on macro-averaged scores for a fairer evaluation, rewarding the classifiers that perform well across the different labels. More details on the rumour stance classification task can be found in the report of the RumourEval shared task [Derczynski et al. 2017].

8.2. Datasets

Work on stance classification has made use of different datasets, although the only dataset that is publicly available is the PHEME stance dataset¹³, which provides tweet-level annotations of stance (support, deny, query, comment) for tweets associated with nine events. Other datasets used in previous work include a dataset with over 10,000 tweets annotated for stance as support, deny or query by [Qazvinian et al. 2011] and the dataset annotated as affirm, deny, neutral, uncodable or unrelated by [Andrews et al. 2016]; however, the latter two are not publicly available.

A dataset released for the Fake News Challenge¹⁴ is also annotated for stance (agrees, disagrees, discusses, unrelated). This dataset is however made of news articles instead of social media posts.

8.3. Approaches to Rumour Stance Classification

Stance classification is well studied in online debates where the aim is to classify the user entries as “for” or “against”. Studies in this respect define stance as an overall position held by a person towards an object, idea or position [Somasundaran and Wiebe 2009; Walker et al. 2012]. Unlike stance classification in online debates, the aim of rumour stance classification is to classify user contributions as, e.g., “supporting”, “denying”, “querying” or “commenting”. However, in the literature the *querying* and *commenting* categories are sometimes omitted or replaced by the “neutral” label that encompasses everything that is not *supporting* or *denying*. The rumour stance classification task has attracted many studies over the past few years. All studies follow a supervised approach, and mainly differ in the way they represent a post and how this representation is used to generate a predictive model, i.e. in the features and in the machine learning approaches used to learn predictive models.

One of the pioneering studies in this task is reported by [Mendoza et al. 2010]. The study involved a human-labelled, non-automated analysis of rumours with established veracity levels to understand the stance that Twitter users express with respect to true and false rumours. The authors looked at fourteen rumours, seven of which turned out to be true and the other seven were proven false. They manually labelled the tweets associated with those rumours with the stance categories “affirms” (supports), “denies”

¹³https://figshare.com/articles/PHEME_rumour_scheme_dataset_journalism_use_case/2068650

¹⁴<http://www.fakenewschallenge.org/>

and “*questions*”. They found that over 95% of tweets associated with true rumours were “*affirms*”, whereas only 4% were “*questions*” and only 0.4% were “*denies*”. This suggested that true rumours are largely supported by other Twitter users. On the other hand, 38% of the tweets associated with false rumours were identified as “*denies*” and 17% as “*questions*”. While false rumours are not denied as often as true rumours are supported, both of these figures suggest that there is indeed a difference in the stances expressed by users towards true and false rumours and that user stances can be indicative of rumour veracity. This study aims to understand the stance categories by manual classification and human analysis, so it does not propose any solution to perform the stance classification task automatically. The first study that tackles the stance classification automatically is reported by [Qazvinian et al. 2011]. In addition to stance classification the authors also perform automatic rumour tracking, as we reported in Section 7. The supervised approach developed for the rumour tracking task is also adopted for the stance classification task. In the rumour stance classification task the tweets are classified as *supporting*, *denying*, *questioning* or *neutral*. In terms of results, observations similar to the ones obtained for the rumour tracker are reported. When all features are used an accuracy of 93.5%, a precision of 94.4% and recall of 90.6% are achieved. Similarly to the rumour tracking task, the best performing features are those belonging to the content category.

Similar to [Qazvinian et al. 2011], the work by [Hamidian and Diab 2015] reports rumour tracking and rumour stance classification by applying supervised machine learning using the dataset created by [Qazvinian et al. 2011]. However, instead of Bayesian classifiers the authors use the J48 decision tree implemented within the Weka platform [Hall et al. 2009]. The features from [Qazvinian et al. 2011] are adopted and extended with time related information and the hashtag itself as a token instead of the semantic content of the hashtag as used by [Qazvinian et al. 2011]. In addition to these features, Hamidian and Diab introduce another feature category: “*pragmatics*”. The pragmatic features include named entities, events, sentiment and emoticons. The evaluation of the performance is cast either as a 1-step problem containing a 6-way classification task (unrelated to rumour, 4 classes of stance and not determined) or as a 2-step problem containing first a 3-way classification task (related to rumour, unrelated to rumour, not determined) and then 4 class classification task (stance classification). The highest performance scores are achieved using the 2-step approach leading to 82.9% F-1 measure compared to 74% with the 1-step approach. The authors also report that the best performing features were the content based features and the least performing ones the network and Twitter specific features. In their recent paper, [Hamidian and Diab 2016] introduce the Tweet Latent Vector (TLV) approach that is obtained by applying the Semantic Textual Similarity model proposed by [Guo and Diab 2012]. The authors compare the TLV approach to their own earlier system as well as to original features of [Qazvinian et al. 2011] and show that the TLV approach outperforms both baselines.

[Liu et al. 2015] follow the resulting investigations of stances in rumours by [Mendoza et al. 2010] and use stance as an additional feature to those reported in related work to tackle the veracity classification problem (see Section 9). For stance classification the authors adopt the approach of [Qazvinian et al. 2011] and compare it with a rule-based method briefly outlined by the authors. They claim that their rule-based approach performed better than the one adopted by previous work and thus use the rule-based stance classification as an additional component in the veracity problem (see Section 9). The experiments were performed on the dataset reported by [Qazvinian et al. 2011]. Unfortunately, the authors do not provide detailed analysis of the performance of the stance classifier.

More recently, [Zeng et al. 2016] enrich the feature sets investigated by earlier studies by features determined through Linguistic Inquiry and Word Count (LIWC) dictionaries [Tausczik and Pennebaker 2010]. They investigate supervised approaches to stance classification using Logistic Regression, Naïve Bayes and Random Forest classification. The authors use their own manually annotated data to classify tweets for stance. However, unlike previous studies, Zeng et al. consider only two classes: affirm and deny. The best results are achieved using a Random Forest classifier, which leads to a performance of 87% in precision, 96.9% in recall, 91.7% in F1-measure and 88.4% in accuracy.

[Lukasik et al. 2016] investigated Gaussian Processes as rumour stance classifier. For the first time the authors also use Brown Clusters to extract the features for each tweet. The authors work on rumour data released by [Zubiaga et al. 2016] and report an accuracy of 67.7%. This result is achieved when the classifier is trained on $n - 1$ rumours and tested on the n^{th} rumour. However, the authors achieve substantially better results when a small proportion from the in-domain data (data from the n^{th} rumour) is included in the training leading to almost 68.6% accuracy. Performance scores differ substantially from those in the studies described above, given that Lukasik et al. tackled classification of stance in new rumours that differ from those in the training set.

Subsequent work has also tackled stance classification for new, unseen rumours. [Zubiaga et al. 2016a] moved away from the classification of tweets in isolation, focusing instead on Twitter ‘conversations’ [Tolmie et al. 2017b] initiated by rumours. They looked at tree-structured conversations initiated by a rumour and followed by tweets responding to it by supporting, denying, querying or commenting on it. To mine the conversational nature of the data, they used Conditional Random Fields (CRF) as a sequential classifier in two different settings: Linear-Chain CRFs and Tree CRFs. Their objective with CRFs was to exploit the discursive nature of the argumentation produced collaboratively by users. Their experiments on eight different datasets of rumours spread during breaking news showed that the discursive characteristics of conversations can be indeed exploited with a sequential classifier to improve on the performance that equivalent, non-sequential classifiers can achieve.

Rumour stance classification for tree structured conversations has also been studied in the RumourEval shared task at SemEval 2017 [Derczynski et al. 2017]. The subtask A consisted of stance classification of individual tweets discussing a rumour within a conversational thread as one of *support*, *deny*, *query*, or *comment*. Eight participants submitted results to this task. Most of the systems viewed this task as a 4-way single tweet classification task, with the exception of the best performing system by [Kochkina et al. 2017], as well as the systems by [Wang et al. 2017] and [Singh et al. 2017]. The winning system addressed the task as a sequential classification problem, where the stance of each tweet takes into consideration the features and labels of the previous tweets. The system by [Singh et al. 2017] takes as input pairs of source and reply tweets, whereas [Wang et al. 2017] addressed class imbalance by decomposing the problem into a two step classification task, first distinguishing between comments and non-comments, to then classify non-comment tweets as one of support, deny or query. Half of the systems employed ensemble classifiers, where classification was obtained through majority voting [Wang et al. 2017; García Lozano et al. 2017; Bahuleyan and Vechtomova 2017; Srivastava et al. 2017]. In some cases the ensembles were hybrid, consisting both of machine learning classifiers and manually created rules, with differential weighting of classifiers for different class labels [Wang et al. 2017; García Lozano et al. 2017; Srivastava et al. 2017]. Three systems used deep learning, with [Kochkina et al. 2017] employing LSTMs for sequential classification, [Chen et al. 2017] using convolutional neural networks (CNN) for obtaining the repre-

sentation of each tweet, assigned a probability for a class by a softmax classifier and [García Lozano et al. 2017] using CNN as one of the classifiers in their hybrid conglomeration. The remaining two systems by [Enayet and El-Beltagy 2017] and [Singh et al. 2017] used support vector machines with a linear and polynomial kernel respectively. Half of the systems invested in elaborate feature engineering, including cue words and expressions denoting Belief, Knowledge, Doubt and Denial [Bahuleyan and Vechtomova 2017] as well as Tweet domain features, including meta-data about users, hashtags and event specific keywords [Wang et al. 2017; Bahuleyan and Vechtomova 2017; Singh et al. 2017; Enayet and El-Beltagy 2017]. The systems with the least elaborate features were [Chen et al. 2017] and [García Lozano et al. 2017] for CNNs (word embeddings), [Srivastava et al. 2017] (sparse word vectors as input to logistic regression) and [Kochkina et al. 2017] (average word vectors, punctuation, similarity between word vectors in current tweet, source tweet and previous tweet, presence of negation, picture, URL). Five out of the eight systems used pre-trained word embeddings, mostly Google News word2vec embeddings¹⁵, whereas [Wang et al. 2017] used four different types of embeddings.

Other related studies that have looked into stance classification not directly applicable to rumour stance classification. While [Zhao et al. 2015] did not study stance classification per se, they developed an approach to look for querying tweets, which is one of the reaction types considered in stance classification. However, the other stance types were not considered and querying tweets were found by matching with manually defined regular expressions, which may not be directly applicable to other stance types. While not focused on rumours, classification of stance towards a target on Twitter was addressed in SemEval-2016 task 6 [Mohammad et al. 2016]. Task A had to determine the stance of tweets towards five targets as ‘favor’, ‘against’ or ‘none’. Task B tested stance detection towards an unlabelled target, which required a weakly supervised or unsupervised approach.

Researchers have also studied the identification of agreement and disagreement in on-line conversations. To classify agreement between question-answer (Q-A) message pairs in fora, [Abbott et al. 2011] used Naive Bayes as the classifier and [Rosenthal and McKeown 2015] used a logistic regression classifier. A sequential classifier like CRF has also been used to detect agreement and disagreement between speakers in broadcast debates [Wang et al. 2011]. It is also worthwhile emphasising that stance classification is different to agreement/disagreement detection, given that in stance classification one has to determine the orientation of a user towards a rumour. Instead, in agreement/disagreement detection, one has to determine if a pair of posts share the same view. In stance classification, one might agree with another user who is denying a rumour and hence they are denying the rumour as well, irrespective of the pairwise agreement.

9. RUMOUR VERACITY CLASSIFICATION

9.1. Definition of the Task and Evaluation

The veracity classification task aims to determine whether a given rumour can be confirmed as true, debunked as false, or its truth value is still to be resolved. Given a set of posts associated with a rumour and, optionally, additional sources related to the rumour, the task consists in assigning one of the following labels to the rumour, $Y \in \{true, false, unverified\}$. Some work has limited the classification to a binary task of determining if a rumour is true or false; however, it is likely that veracity value will remain uncertain for some rumours. Optionally, the classifier can also output, along

¹⁵<https://github.com/mmihaltz/word2vec-GoogleNews-vectors>

with the veracity label, the confidence with which the label has been assigned, usually ranging from 0 to 1.

The outcome of the veracity classification task is usually evaluated either using the accuracy measure that computes the ratio of correct classifications, or using a combination of precision, recall and F1 score for the three categories.

9.2. Datasets

The dataset produced for RumourEval 2017 [Derczynski et al. 2017], a shared task that took place at SemEval 2017, includes over 300 rumours annotated for veracity as one of *true*, *false* or *unverified*. Another dataset suitable for veracity classification is the one released by [Kwon et al. 2017], which includes 51 true rumours and 60 false rumours. Each rumour includes a stream of tweets associated with it.

Other datasets, such as that by [Qazvinian et al. 2011], are not suitable for veracity classification, as all the rumours are false.

9.3. Approaches to Rumour Veracity Classification

The vast majority of research dealing with social media rumours has focused on veracity classification, which is the crucial and ultimate goal of determining the truth value of a circulating rumour. This work generally assumes that rumours have already been identified or input by a human. Therefore, most of the previous work skips the preceding components of a rumour classification system, especially the rumour detection component that identifies candidate rumours to be input to the veracity classification system.

Work by [Castillo et al. 2011] initiated research in this direction of determining the veracity of social media content. Although the authors did not directly tackle the veracity of rumours but rather their credibility perceptions, i.e., determination of the believability or authority of its source [Zhang et al. 2015]. However, others report that veracity is related to authority [Association et al. 2001; Oh et al. 2013] and hence Castillo et al.'s work has been considered as a reference by many in subsequent work on veracity classification.

To study credibility perceptions, [Castillo et al. 2011] distinguish two types of microblog posts: 'NEWS', which report an event or fact that can be of interest to others, and 'CHAT', which is a message that is purely based on personal/subjective opinions and/or conversations among friends. Microblogs categorised as NEWS are analysed for rumour credibility. Decision trees based on J48 are used to train classifiers and these are used to classify microblogs into NEWS and CHAT categories. The microblogs in the NEWS category are further analysed for credibility – for this task the authors report that they used various other machine learning approaches, such as Bayesian networks and SVM classifiers, but mention that decision trees based on J48 were superior. In the experiments microblogs collected from Twitter are used. These are manually annotated using the Mechanical Turk. The authors use four categories of features: message-based, user-based, topic-based and propagation-based features. The message-based features consider characteristics of messages such as the length of a message, whether the message contains exclamation/question marks, number of positive/negative sentiment words, whether the message contains a hashtag, and whether it is a retweet. User-based features entail information about the user such as registration age, number of followers, number of followees and the number of tweets the user has authored in the past. Topic-based features aggregate information from the previous two feature types, such as the fraction of tweets that contain URLs, the fraction of tweets with hashtags, etc. Finally, the propagation-based features consider characteristics related to the messaging tree, such as depth of the retweet tree or the number of initial tweets on a topic. In the NEWS/CHAT classification task the authors report

89.2% accuracy, 89.1% precision, 89.1% recall and 89.1% F1-measure. In the credibility classification task, an accuracy of 86% is reported (the same figure is reported for precision/recall and F-1 measure). Despite the fact that this approach was designed for classification of credibility perceptions, the features utilised in this work have subsequently been exploited for veracity classification too.

Most research, however, has dealt with veracity classification. [Kwon et al. 2013] propose new set of feature categories: temporal, structural and linguistic. The temporal features aim to capture how rumours spread over time. The structural features model the connectivity between users who posted about the rumour. Finally, the linguistic features are obtained through the Linguistic Inquiry and Word Count (LIWC) dictionaries [Tausczik and Pennebaker 2010]. As a baseline classifier, features proposed by [Castillo et al. 2011] are adopted. Using Random Forest and Logistic Regression, the authors perform feature selection to find the most significant ones. Using these features and three different classifiers (Decision tree, Random Forest and SVM) they then perform rumour veracity classification. The results show that for both selection of significant features and subsequent classification, a Random Forest classifier performed best in terms of accuracy (90%), precision (93.5%), recall (89.2%) and F1-measure (89.3%). The best results using the baseline features adopted from [Castillo et al. 2011] are obtained using a SVM with 81.1% accuracy, 89.1% precision, 75.3% recall and 78.8% F1-measure. The authors also show that a combination of significant features identified by Random Forest and baseline features lead to performance degradation. More recently, [Kwon et al. 2017] analyse feature stability over time and report that structural and temporal features distinguish true from false rumours over a long-term window. However, the authors also report that these are not available in early stage of rumour propagation but only later on. In contrast, user and linguistic features are an alternative when the task is to determine rumour veracity as early as possible.

[Yang et al. 2012] tackle the veracity of microblogs on the Chinese microblogging platform Sina Weibo. The authors adopt features from earlier studies discussed above and extend them with two more features: client-based and location-based features. The client-based features include information about the software that was used to perform the messaging. The location-based features include information relating to whether the message was sent from within the same country where the event happened or not. The authors report that adding these two features on top of earlier reported features leads to a substantial boost of accuracy. For instance, adding the two features on top of the propagation-based features reported by [Castillo et al. 2011] leads to an increase of 6.3% in accuracy. However, the authors do not combine all the features and report results on them. For the classification task, the authors use SVM with the RBF kernel [Buhmann 2003]. Another study that tackles rumours in Sina Weibo is reported by [Yang et al. 2015]. Unlike the others, the authors make use of the reviews or comments attached to the source tweet. Traditional features discussed so far are used, but they also incorporate network features (creating a social network based on the comment providers) derived from comments to perform the rumour veracity classification task. It is shown that when the network feature is added to the traditional features the results improve substantially.

[Liu et al. 2015] use approaches reported by [Yang et al. 2012] and [Castillo et al. 2011] as baseline systems and compare them against their proposed approach that make use of so called “verification features”. These features are determined based on insights from journalists and include source credibility, source identification, source diversity, source and witness location, event propagation and belief identification. In belief identification results of rumour stance classification are used as features. The authors show that the proposed approach outperforms the two baselines. They also

show that, when adding the belief identification to the other features, the results are significantly better than when not adding them to the feature set. The best results range from 78% to 89% accuracy depending on how many tweets are used to verify the rumour (5 tweets to 400 tweets). The experiments are performed on the author's own dataset using SVM classification. The authors also report having investigated Random Forest and Decision Trees but SVM gave the best results, although no further details are provided on this comparison.

[Ma et al. 2015] proposed to model features over time. The authors adopt features from earlier studies as well as machine learning approaches used in those studies (J48, SVM with the RBF kernel). Experiments are performed on datasets from both Twitter and Sina Weibo. Ma et al. use SVM with linear kernel and report that this linear SVM combined with the proposed approach that models the features over time leads to best performance. On the Twitter dataset reported by [Castillo et al. 2011] the authors report 89% accuracy. For Sina Weibo, the authors collect their own dataset and run existing approaches on them. The proposed setting reaches an accuracy of 84.6% where decision trees with J48 leads to 77.4%, SVM with the RBF kernel to 77.9% and random forests to 81.5%.

[Wu et al. 2015] extract features from message propagation trees. Three categories of features are considered: message-based, user-based and report-based. Two methods reported by earlier studies [Castillo et al. 2011] and [Yang et al. 2012] are adopted for the evaluation. The machine learning approach chosen by the authors is an SVM with a hybrid kernel technique consisting of random walk kernel [Borgwardt et al. 2005] and an RBF kernel. The results reported are in favour of the proposed hybrid approach leading to 91% accuracy. The baselines achieve 85.4% [Castillo et al. 2011] and 77.2% accuracy [Yang et al. 2012]. In the experiments the authors use rumours with at least 100 reposts. This opens the question as to how well the proposed approach will perform when it is applied to newly emerging rumours where there are only few posts available. The idea of message propagation is also investigated by [Wang and Terano 2015] in combination with pattern matching. In addition, the information inferred from a stance classifier is integrated in the classification process. They propose social graphs to model the interaction between users and so identify influential rumour spreaders. The graph entails information about familiarity measured by the number of contacts such as retweets, replies and comments between two users, activeness measured by the number of days a user has sent out messages, similarity measured by gender and location similarity between two users and trustworthiness measured by whether the user is verified or not. These four factors are merged in a linear model and hence the model is used to weight the link between two users in the social graph. Using a new proposed metric influential spreaders are used to determine rumours.

[Vosoughi 2015] tackles veracity classification task using three categories of features (linguistic, user oriented and temporal propagation related features) and speech recognition inspired machine learning approaches, such as Dynamic Time Wrapping (DTW) and Hidden Markov Models (HMMs). Evaluations are performed on Twitter data gathered by the author. Results show that HMMs with 75% accuracy are superior to DTWs that lead to only 71% accuracy. The authors also report that the best performing features are those in the temporal propagation category leading to 70% accuracy. The linguistic features lead to 64% accuracy and the user oriented features to 65% accuracy. It is also worthwhile noting that the authors, like [Wu et al. 2015], work with rumours that have at least a good volume of tweets, in this case 1,000 tweets.

[Giasemidis et al. 2016] report experiments run on 100 million tweets associated with 72 different rumours. Features and machine learning classifiers used in previous work are adopted in this case. The authors report 96.6% classification accuracy and 97% F1 score which are achieved using decision trees.

[Chen et al. 2016] approach the rumour veracity classification from a different angle. The authors treat it as an anomaly detection problem where false rumours are regarded as anomalies. Several features related to the content, crowd opinion and post propagation are used along with a factor analysis. Euclidean distance and cosine similarity are proposed to describe the deviation degree and posts with high deviation degree are marked as rumours. Comparisons are made with respect to well-known clustering approaches, such as K-means, and the reported results show significantly improved performance.

[Chang et al. 2016] put the emphasis on the characteristics of users who post the rumours to determine the veracity. The authors focus on tweets discussing news. Such tweets are first clustered using simple heuristics, e.g., all posts linking to the same news article are grouped together. Based on rules and heuristics, 'extreme users' are determined – users who match the heuristics, such as number of followers, etc., of users that are likely to post false rumours. If a cluster of posts contains a number of extreme users exceeding a predefined threshold then it is marked as a false rumour cluster. Authors report rules which led to 80% precision and recall.

[Chua and Banerjee 2016] published an analysis of various features on the tweet veracity classification task. The authors analysed six categories of features: comprehensibility, sentiment, time-orientation, quantitative details, writing style and topic. Rumours gathered by the authors are used along with the binomial logistic regression to tackle the task in a supervised fashion. Unlike previous studies, Chua et al. only report features that are significantly important rather than an indication of the overall performance of the classifier. These features are: negation words (comprehensibility category), past, present, future POS in the tweets (time-orientation category), discrepancy, sweat and exclusion features (writing style category) and, finally, home, leisure, religion and sex topic features (topic category). In a similar vein, [Ma et al. 2017] investigated the performance difference between bag-of-words (BoW) and word embedding representation of post contents and conclude that the BoW representation was superior to the embedding variant.

[Zhang et al. 2015] investigate rumour veracity classification within the health domain. Using data obtained from liuyanbaike.com (a Chinese rumour debunking platform), the authors investigate the correlation between features and veracity of rumours (true or false) based on logistic regression. They report that features like mention of numbers, the source the rumour originated from and hyperlinks, positively correlate with true rumours and rumours containing some wishes are positively correlated with false rumours. If images are included in the rumours then those were negatively correlated with true rumours. Finally, the authors report that the foreign source feature (whether a foreign source was used to support the rumour or not) was not correlated at all with rumour veracity.

[Qin et al. 2016] aim to detect new rumours and propose two new feature categories to achieve this. In the first category, posts containing new pieces of information that are unconfirmed with respect to some news event are considered as rumours. In the second feature category, later posts that repeat the same information as the earlier ones marked as rumour are also considered as rumours. The authors report significantly better results than baseline approaches when the aim is to determine veracity of rumours early on (in their particular case, in less than 12 hours).

Unlike the previous studies, [Tong et al. 2017] aim at blocking rumours rather than detecting them or marking tweets as true or false. Motivated by the fact that later corrections are not as effective, the authors argue that the first post seen by a user is influential for their future opinion and thus it is important to show users rumours only once they are confirmed to be true. Based on this they propose a reverse-tuple based

randomised algorithm to block rumours. The algorithm aims at producing positive seeds to be shown to users first.

Rumour veracity classification has also been studied in the RumourEval shared task at SemEval 2017 [Derczynski et al. 2017]. Subtask B consisted in determining if each of the rumours in the dataset were true, false or remained unverified. It considered two different settings, one *closed* where participants could not make use of external knowledge bases and another *open* where use of external resources was allowed. Five participants submitted results to this subtask. Participants viewed the task either as either a three-way [Enayet and El-Beltagy 2017; Wang et al. 2017; Singh et al. 2017] or two-way [Chen et al. 2017; Srivastava et al. 2017] single tweet classification task. The methods used mostly the same features and classifiers as used in subtask A (see Section 8), although some added features more specific to the distribution of stance labels in the tweets replying to the source tweet (for example, the best performing system in this task [Enayet and El-Beltagy 2017] considered the percentage of reply tweets classified as either support, deny or query).

10. APPLICATIONS

There have been numerous efforts by both industry and the scientific community to deal with social media rumour detection and verification, ranging from ongoing research projects to fully-fledged applications. The following are some notable examples:

- **PHEME**¹⁶ [Derczynski and Bontcheva 2014] is a 3-year research project funded by the European Commission, which ran from 2014-2017, studying natural language processing techniques for dealing with rumour detection and resolution. Publications produced as part of this project include rumour detection [Zubiaga et al. 2016b], stance classification [Lukasik et al. 2015a; Lukasik et al. 2016; Zubiaga et al. 2016a], contradiction detection [Lendvai et al. 2016a; Lendvai and Reichel 2016], ontological modelling of rumours [Declerck et al. 2015], visualisation [Lendvai et al. 2016b], analysis of social media rumours [Zubiaga et al. 2016] and studies of journalistic practices of the use of user-generated content [Tolmie et al. 2017a].
- **Emergent**¹⁷ is a data-driven, real-time, web-based rumour tracker. The system automatically tracks social media mentions of URLs associated rumours, however, the identification of rumours and selection of URLs associated with those requires human input and has not been automated. It is part of a research project led by Craig Silverman, partnering with the Tow Center for Digital Journalism at Columbia University, which focuses on how unverified information and rumour are reported in the media. The outcome of this project was published in a report on best practices for debunking misinformation [Silverman 2015a].
- **RumorLens**¹⁸ [Resnick et al. 2014] is a one year research project that ran in 2014, funded by Google. It focused on building a tool to aid journalists in finding posts that spread or correct a particular rumour on Twitter, by exploring the size of the audiences that those posts have reached. More details on the rumour detection system developed in this project were published in [Zhao et al. 2015].
- **TwitterTrails**¹⁹ [Finn et al. 2014] is a project in the Social Informatics Lab at Wellesley College. Twitter Trails is an interactive, web-based tool that allows users to investigate the origin and propagation characteristics of a rumour and its refutation, if any, on Twitter. Visualisations of burst activity, propagation timeline, retweet

¹⁶<http://www.pheme.eu/>

¹⁷<http://www.emergent.info/>

¹⁸<https://www.si.umich.edu/research/research-projects/rumorlens>

¹⁹<http://twittertrails.com/>

and co-retweeted networks help its users trace the spread of a story. It collects relevant tweets and automatically answers several important questions regarding a rumour: its originator, burst characteristics, propagators and main actors according to the audience. In addition, it computes and reports the rumour's level of visibility and, as an example of the power of crowdsourcing, the audience's skepticism towards it which correlates with the rumour's credibility. The project has produced a number of publications (cf. [Finn et al. 2015; Metaxas et al. 2015]) exploring and characterising the diffusion of rumours.

- **RumourFlow** [Dang et al. 2016b] is a framework that designs, adopts and implements multiple visualisations and modelling tools that can be integrated to reveal rumour contents and participants activity, both within a rumour and across different rumours. The approach supports analysts in drawing hypotheses regarding rumour propagation.
- **Hoaxy**²⁰ [Shao et al. 2016] is a platform for the collection, detection and analysis of online misinformation and its related fact checking efforts.
- **REVEAL**²¹ is a 3 year project (2013–2016) funded by the European Commission. It is concerned with verification of social media content from a journalistic and enterprise perspective, especially focusing on image verification. The project has produced a number of publications on journalistic verification practices concerning social media [Brandtzaeg et al. 2016], social media verification approaches [Andreadou et al. 2015] and approaches to track down the location of social media users [Middleton and Krivcovs 2016].
- **InVID**²² (In Video Veritas) is a Horizon 2020 project, funded by the European Commission (2017–2020), which will build a platform providing services to detect, authenticate and check the reliability and accuracy of newsworthy video files and video content spread via social media.
- **CrossCheck**²³ is a collaborative verification project led by First Draft and Google News Lab, in collaboration with a number of newsrooms in France, to fight misinformation, with an initial focus on the French presidential election.
- **Décodex**²⁴ is an online database by the French news organisation Le Monde, which allows to check the reliability of news in an Internet domain, warning about a number of satire news and unreliable sites.
- **Check**²⁵ is a verification platform that offers newsrooms the possibility to verify breaking news content online. The platform is not openly available yet, but there is a form to register interest.
- **ClaimBuster**²⁶ is a project aiming to perform live fact-checking. The demo application shows check-worthy claims identified by the system for the 2016 US election, and it allows the user to input their own text to find factual claims. Details of the project have been published in [Hassan et al. 2015].
- **Una Hakika**²⁷ is a Kenyan project dealing with misinformation and disinformation. It offers a search engine to look for rumours, as well as an API for data collection. It is manually updated with new stories.

²⁰<http://hoaxy.iuni.iu.edu/>

²¹<http://revealproject.eu/>

²²<http://www.invid-project.eu/>

²³<https://firstdraftnews.com/crosscheck-launches/>

²⁴<http://www.lemonde.fr/verification/>

²⁵<https://meedan.com/en/check/>

²⁶<http://idir-server2.uta.edu/claimbuster>

²⁷<http://www.unahakika.org/>

- **Seriously Rapid Source Review**²⁸ [Diakopoulos et al. 2012] is a system that incorporates a number of advanced aggregations, computations and cues that can be helpful for journalists to find and assess sources in Twitter around breaking news events, such as finding eyewitnesses on the ground. Finding eyewitnesses can be helpful to get first hand reports that provide evidence to either confirm or debunk rumours.
- **TweetCred**²⁹ [Gupta and Kumaraguru 2012; Gupta et al. 2014] is a real-time, web-based system to assess credibility of content on Twitter. While the system does not determine the veracity of stories, it provides a credibility rating between 1 to 7 for each tweet on the Twitter timeline.

11. DISCUSSION: SUMMARY AND FUTURE RESEARCH DIRECTIONS

Research on the development of rumour detection and verification tools has become increasingly popular as social media penetration has increased, enabling both ordinary users and professional practitioners to gather news and facts in a real-time fashion, but with the problematic side effect of the diffusion of information of unverified nature. This survey has summarised studies reported in the scientific literature towards the development of rumour classification systems, defining and characterising social media rumours and has described the different approaches to the development of their four main components: (1) rumour detection, (2) rumour tracking, (3) rumour stance classification, and (4) rumour veracity classification. In so doing, the survey provides a guide to the state-of-the-art in the development of these components. In what follows we review the progress achieved so far, the shortcomings of existing systems, outline suggestions for future research, and comment on the applicability and generalisability of rumour classification systems to other kinds of misleading information that also spread in social media.

Research in detection and resolution of rumours has progressed substantially since the proliferation of social media as a platform for information and news gathering. A range of studies have taken very different approaches to understanding and characterising social rumours and this diversity helps to shed light on the future development of rumour classification systems. Research has been conducted in all four of the components that comprise a rumour classification system, although most have focused on the two last components of the pipeline, namely rumour stance classification and veracity classification. Despite substantial progress in the research field, as shown in this survey, we also show that this is still an open research problem that needs further study. We examine the main open research challenges in the next section.

11.1. Open Challenges and Future Research Directions

In recent years, research in rumour classification has largely focused on the later stages of the pipeline, namely rumour stance classification and veracity classification. These are crucial stages, however, they cannot be used without performing the preceding tasks of detecting rumours and tracking posts associated with those rumours. The latter has generally been skipped in previous work, either leaving the development of those components for future work or assuming that rumours and associated posts are input by a human. Aiming to alleviate these initial tasks by avoiding relying entirely on the human-in-the-loop, we argue that future research should focus on rumour detection and tracking.

An important limitation towards the development of rumour classification systems has been the dearth of publicly available datasets. Along with the recently published

²⁸<http://www.nickdiakopoulos.com/2012/01/24/finding-news-sources-in-social-media/>

²⁹<http://twittdigest.iiitd.edu.in/TweetCred/>

datasets that we have listed in this survey, we encourage researchers to release their own datasets so as to enable further research over different datasets and so permit the scientific community to compare their approaches with one another.

While many have attempted to automatically determine the veracity value of a rumour, a system that simply outputs the final decision on veracity may not always be sufficient, given that the classifier will inevitably make errors. To make the output of a veracity classifier more reliable, we argue that the system needs to provide a richer output that also includes the reason for the decision [Procter et al. 2013b]. A veracity classifier that outputs not only the automatically determined veracity score, but also links to sources where this decision can be corroborated, will be more robust in that it will enable the user to assess the reliability of the classifier’s decision and – if found wanting – to ignore it. The output of a veracity classifier can be enriched, for instance, by using the output of the stance classifier to choose a few supporting and opposing views that can be presented to the user as a summary. Given that achieving a perfectly accurate veracity classifier is an unlikely goal, we argue that research in this direction should focus especially on finding information sources that facilitate the end user to make their own judgement of rumour veracity.

Another caveat of existing veracity classification systems is that they have focused on determining veracity regardless of rumours being resolved. Where rumours have not yet been resolved, the veracity classification task becomes then a prediction task, which may not be reliable for an end user given the lack of evidence to support the system’s decision. As rumours have an unverified status in which determining veracity is hard or requires involvement of authoritative sources, future research should look into temporality of rumour veracity determination, potentially attempting to determine veracity soon after evidence can be found.

11.2. Rumours, Hoaxes, Misinformation, Disinformation, Fake News

In this survey we have covered previous efforts towards the development of a rumour classification system that can detect, and resolve the veracity of, rumours. As defined in Section 1.1, rumours refer to pieces of information that start off as unverified statements. A rumour’s veracity value is unverifiable in the early stages, while being subsequently resolved as true or false in a relatively short period of time, or it can also remain unverified for a long time. A number of similar terms are also used in related literature, which have distinct characteristics but also commonalities with rumours.

The term misinformation is used to refer to circulating information that is accidentally false as a consequence of an honest mistake, while disinformation refers to information that is deliberately false [Hernon 1995]. Rumours can fall in either of these two categories, depending on the intent of the source; however, the main difference is that rumours are not necessarily false, but may turn out to be true. A rumour that is eventually debunked can then be categorised into misinformation or disinformation depending on the intent of the source.

Unlike rumours, hoaxes and fake news are, by definition, always false and can be seen as specific types of disinformation. While it is usually used to refer to any fabricated falsehood indistinctly, a hoax is more rigorously defined as a false story used to masquerade the truth, originating from the verb *hocus*, meaning “to cheat” [Nares 1822]. Fake news are a specific type of hoax, usually spread through news outlets that are intended to gain politically or financially [Hunt 2016]. However, terms like *fake news* are widely being used to refer to different types of inaccurate information, while not necessarily adhering to any specific type of misinformation. As [Wardle 2017] suggested, the term fake news is being used to refer to seven types of misinformation: false connection, false context, manipulated content, satire or parody, misleading content, imposter content and fabricated content.

The approaches described in this survey are designed to tackle the problem of rumour. Further research is needed to study their applicability to other phenomena, such as hoaxes and fake news. However, we believe that some of the underlying commonalities between rumours, hoaxes and fake news suggest that rumour research has an important contribution to make the new challenges posed by these more recent phenomena.

11.3. Further Reading

For more discussion on the issues we cover in this survey, we recommend the special issue on trust and veracity of information on social media of the ACM TOIS journal [Papadopoulos et al. 2016; Rijke 2016], Full Fact's report on *The State of Automated Factchecking* [Babakar and Moy 2016], reports and discussion on rumours on Snopes³⁰ and Craig Silverman's books on rumours and journalistic verification practices [Silverman 2013; 2015a; 2015b]. We also recommend keeping track of ongoing initiatives by the Knight Center for Journalism in the Americas³¹ and the European Journalism Centre³², as well as signing up for relevant newsletters such as Craig Silverman's on online rumours, fake news and misinformation³³ and Poynter and American Press Institute's 'The Week in Fact-Checking'³⁴.

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³⁰<http://www.snopes.com/>

³¹<https://knightcenter.utexas.edu/>

³²<http://ejc.net/>

³³<http://us2.campaign-archive1.com/?u=657b595bbd3c63e045787f019&id=2208e04aa6>

³⁴<http://us9.campaign-archive1.com/?u=79fa45ed20ff84851c3b9cd63&id=02624abd8b>

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